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Decentralized route guidance architectures with user preferences in urban transportation networks

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Abstract

In the last decades, the increase of traffic and the limited capacity of urban networks, has led to the development of algorithms for traffic management and route guidance. The route guidance systems may cause a well-known dilemma by suggesting the same path to too many drivers. We propose a multiple path routing algorithm, in which each vehicle computes its own route on the basis of (*i*) its specific settings reflecting user's preferences/constraints and (*ii*) traffic information provided by the reference station. Our aim is to propose a solution that represents a good trade off between single user satisfaction and system optimum.

Keywords: Shortest path; Intelligent Transportation Systems; Route Guidance.

1. Introduction

Due to the increase of the traffic and to the limited capacity of urban traffic networks, in the last few years traffic management and route guidance algorithms are becoming more and more widely adopted, also due to the reduced price of GPS terminals. Several studies show that choosing a path without relying on any information provided by GPS and/or guidance algorithms may result in travel times between 6% and 19% longer than necessary.

However, one of the main challenges for the correct performing of the transportations in a given area is the implementation of effective *Intelligent Transport Systems* (ITS), able to suitably handle the routing of vehicles by considering both the time and space dimensions.

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In the literature, different approaches for in-car navigation systems have been proposed. The simplest devices perform *static* guidance (Bottom 2000), i.e., the information is not frequently updated. The most common systems only compute shortest paths, with exact or approximated algorithms, considering travel time, geographic distance, or other appropriate measures; moreover, they provide information to drivers who do not know the area well. More sophisticated route guidance systems make use of information on current conditions in the traffic network. The communication with reference station is fundamental. There are two different types of communication one-way and two-ways. In one way case the user can calculated more realistic shortest path based on current road conditions, determined through sensors placed in the network and connected to a central station. With bidirectional communication equipment, the information is exchanged between users and central station, the station would receive users' current positions and destinations, and it can compute some kind of traffic assignment, the routes would be randomly assigned to real drivers and transmitted back to the route guidance devices.

The knowledge of the current traffic conditions is the basis of *reactive* guidance systems [(Papageorgiou, 1990), (Ben-Akiva et al, 1996)]. In reactive guidance, it is possible to respond quickly to demand changes or incidents because no predictions are used. The recommendation provided to drivers at any given time is based on the situation of traffic at that time. The *anticipatory* guidance predicts future demands and traffic conditions and gives recommendations accordingly [(Kaysi et al, 1995), (Ben-Akiva et al, 1985)]. The issue is how future conditions should be predicted. These route guidance systems must predict how users will behave if they follow the recommendation or not, for a correct prediction. According to Bottom (2000), there is no consensus in the community on which of the latter two approaches— reactive or anticipatory—should be used in practice.

Thus, *Route Guidance* (RG) systems have to take into account the overall road usage to improve traffic management, avoiding oversaturation phenomena see Adler and Blue (1998). This can be realized by providing the RG systems with multiple path routing embedded algorithms in order to split vehicles over several paths [(Beccaria et Bolelli, 1992), (Henry et al, 1991), (Adacher et al, 2007)].

Different approaches have been proposed to deal with multiple path routing. Rilett and Van Aerde (1991) suggest adding individual random error terms to the road travel times by a central controller, in order to lead each vehicle to choose different paths. Lee (1994) computes k shortest paths every ten minutes and then distributes vehicles over them every two minutes, considering the current travel times on these paths.

Mäohring et al. (1999) have proposed a constrained system optimum approach, where each driver is routed along a path that is not too far from its *normal length*, being the normal length of a path an appropriate measure in terms of time or distance. The user equilibrium approach minimizes the individual journey time, routing vehicles along paths, such that no vehicle can run a quicker path through the network by unilaterally changing its choice (see Fresz, 1985).

The relation between the two approaches was investigated by Roughgarden and Tardos (2000), showing that the user equilibrium approach often proposes solutions far from the minimization of the total optimum travel time of the system.

If from one side the widespread adoption of RG systems contributes to the reduction of the congestions and to an effective exploitation of the network, from the other side it is envisaged by many simulations that the benefits of such systems may be nullified as the number of users overcomes a certain threshold. In fact, suggesting the same path to too many users, RG systems may eventually exacerbate the congestion of the network.

An approach aimed at minimizing the overall travel time may also be unfeasible for similar reasons. In fact, while some users might be given with the optimum path, some others might be required to follow much longer paths, leading to a great dissatisfaction and eventually to they may decide to abandon the RG system.

The above approach is indeed highly discriminatory in that it may favor some users and penalize others.

Other approaches in the literature, unfortunately, may result in very inefficient global travel time while trying to satisfy the single users.

In this paper, based on the previous works (Adacher et al, 2007, 2009), we propose an approach aimed at solving such a dilemma by explicitly taking into account a *preference parameter* representing the attitude

towards risk of the user, i.e., by letting the users specify to which extent the path assigned may be degraded with respect to the theoretical minimum path, thus accepting sub-optimal paths in order to avoid congestions.

Unlike other approaches, by involving the user in the decision, the blame for the eventual choice of a long path is no more on the system but on the user himself. As a consequence, a dissatisfied user may change its choice of the parameter, rather than quitting using the system.

Moreover, we provide different methodologies for the users to choose an alternative path, and the resulting route is a mediation between the optimal and the alternative path, based on the preference parameter of each agent.

In Adacher and Meloni (2005) and Adacher et al (2007) a hierarchical structure with two different levels is adopted: a high level, where a reference station collects all information related to the traffic on the network and a local level, represented by a set of vehicles connected to the reference station.

It Adacher et al (2009) however, some simplifications were made, in that the strategies for the prediction of flow were based on a high level representation of the network (i.e., decomposing the network in macro-areas or sectors).

In this work, a decentralized approach is adopted, and decisions are taken based on partial information when dealing with large amount of data. With respect to Adacher et al (2007, 2009), a new set of calculation methods of the predicted flow are presented, as well as a categorization of the users based on both the parameter chosen and the method adopted for the flow prediction. Such a profiling may help the users for the choice of their intended behavior; in fact, choosing a profile like “smart”, “indifferent”, “pessimistic” or “optimistic” may be much more appealing and easy for the users, rather than actually specifying a numeric value for the parameter and choosing a flow prediction methodology.

Our aim is to provide a solution that represents a good trade-off between single users satisfaction and global utilization of the network.

The paper is organized as follows. In Section 2, we define the problem and its features and in Section 3 we describe the proposed decentralized approach and the multiple path routing algorithm based on the setting of two parameters for each user. Finally, in Section 4, where we briefly report on preliminary computational results and in Section 5 some conclusive remarks and future work directions are reported.

2. Problem Statement

Let an urban traffic network, described in terms of a directed graph $G = (N, A, U)$ where N is the set of nodes, A is the set of edges and U is the set of users. Specifically, each edge $a \in A$ is a quadruple in the form:

$$a = \{F_a, c_a, d_a, t_a(F_a, c_a, d_a)\} \tag{1}$$

where F_a, c_a and d_a represent, respectively, the current traffic flow and the capacity of the edge in terms of vehicles per time unit and the distance between the two endpoints of the edge. The function $t_a(F_a, c_a, d_a)$ characterizes the edge travel time depending on the current traffic, on the capacity and length of the arc.

Among the possible choices for the function t_a, in this paper the function defined by the U.S. Bureau of Public Roads, one of the most adopted one, is considered:

$$t_a(F_a, c_a, d_a) = d_a \ t_a^0 \left[1 + \gamma \ \left(\frac{F_a}{c_a}\right)^{\beta}\right] \tag{2}$$

where $t_a^0 > 0$ is the travel time of link a in the uncongested network and $\gamma > 0, \beta > 0$ are parameters to be set like suggested in [8].

Each user $u \in U$ is characterized by the couple $\{o_u, d_u\}$ where $o_u, d_u \in N$ are the origin and the destination for the user u, respectively. The *route guidance* problem consists in finding a route assignment for each user $u \in U$.

In the following section we will describe a decentralized solution to the problem at hand that is aimed to avoid oversaturation phenomena, while trying to reduce the dissatisfaction due to the assignment of long paths.

The proposed solution is based on the preferences and attitude towards risk of the different users, which is used as a parameter for the choice of their route.

3. Decentralized route guidance with user constrains

We want to dispatch the users over the network by eventually exploiting several paths, so that the congestions are avoided; at the same time, we want to take such decisions based on the specified preferences of each user, so that they might not be discouraged in using the RG system again.

In this Section, we provide a decentralized solution for the route guidance problem considering a set of user specified parameters. Specifically, we let each user computes his shortest path considering personal graph, whose edges represent a mediation, based on a parameter specified by the user, between the theoretical travel time and the expected travel time according to one out of several potential flow computation methodologies, again, according to the preferences of the user.

To this end, let a *preference parameter* $\alpha_u \in [0,1]$ and a *potential flow strategy parameter* $p_u \in \{1, \dots, h\}$, where h is the number of potential flow computation methodologies considered, each user fixes these two parameters.

In order to compute their paths, the users need global information provided by the system. Specifically, each user u is provided with the sub-network $G_u = (N_u, A_u, U_u)$, where nodes N_u and edges A_u are involved in all candidate paths from o_u to d_u and U_u set of potential users:

$$U_u = \{v : o_v = o_u \; and \; d_v = d_u\} \tag{3}$$

Note that, in this way, the user u knows the number $|U_u|$ of users with the same origin and destination.

Based on G_u each user is able to compute an expected travel time t_e (i.e., a perturbation of the travel time) for each edge $a \in A_u$ by considering the following two quantities:

- The current flow F_a, calculated on the bases of all users that are on the network with a fixed route, without considering the potential users;
- The *potential flow* F_p, which represents the flow related to users that are waiting for their personal route, but have already requested information on the traffic network, specifying their origin o and destination d. It considers the expectancy for the user u of the flow generated by the potential users, according to a given strategy specified by the parameter p_u.

Based on the above quantities, the expected travel time t_e is given by the following function:

$$t_e\left(F_a, F_p(a), c_a, d_a, \alpha_u\right) = t_a\left(\alpha_u F_a + (1-\alpha_u)\left(F_a + F_p(a)\right), c_a, d_a\right) \tag{4}$$

In other words, the flow is assumed to be a convex combination of the current flow F_a and the overall flow $F_a + F_p(a)$ including all the users (current and potential one), based on the preference parameter α_u. The expected travel time is then computed according to Eq. (2).

In the following, we will discuss the proposed strategies for potential flow computation and the user profiling aimed at simplifying the choice of the parameters for the users.

3.1 Potential flow computation methods

The potential flow represents all users that have not yet calculated and communicated their individual route, but have already requested information on the traffic network, specifying their origin o and destination d.

Since such vehicles contribute to the traffic flow over the network, estimating their effect is highly valuable.

In this paper we consider $h = 4$ different methodologies for the computation of the potential flow $F_p(a)$.

1 - Stochastic potential flow. The current flow of each edge $a \in A_u$ is perturbed with a random number $\rho \in [0,1]$ and the potential flow is calculated in the following way:

$$F_p(a) = \rho[c_a - F_a] \tag{5}$$

In this way a choice of $\rho = 1$ implies that the potential flow assumes its maximum value and the arc is saturated; conversely, $\rho = 0$ implies that the potential flow is null and the potential users are not considered.

2 - Shortest path potential flow. For each user u the theoretical shortest path is computed assuming a null potential flow. Then, for each edge a in the shortest path the potential flow is computed assuming that the users in U_u will follow the shortest path, i.e.:

$$F_p(a) = F(a, |U_u|) \tag{6}$$

where $F(a, |U_u|)$ is the flow over the edge a generated by the users in U_u.

3 - Shortest path neighborhood potential flow. For each user u the theoretical shortest path is computed assuming a null potential flow. Then, for each node n_i in the shortest path (except the goal node) we consider the set $\{a_{i0}, a_{i1}, \dots, a_{im}\}$ of all outgoing edges of node n_i, where a_{i0} belongs to the shortest path and the others are not belonging to the shortest path. We choose a random number $\rho \in [0,1]$ and increase the travel time of each arc in $\{a_{i0}, a_{i1}, \dots, a_{im}\}$ assuming that a random fraction of the users in U_u will follow the shortest path, while the others will uniformly split over the remaining outgoing links i.e.:

$$F_p(a_{i0}) = \rho F(a_{i0}, |U_u|) \tag{7}$$

$$F_p(a_{ij}) = \frac{1-\rho}{m} F(a_{ij}, |U_u|), \; j = 1, \dots, m \tag{8}$$

In order to explain the following methods, the concept of edge betweenness is reported.

The *edge betweenness* [20,21] is a centrality measure of an arc in a graph. It is a synthetic index that represents the fraction of shortest paths to which a given edge belongs considering every possible shortest path for every possible choice of origin and destination nodes. More in detail, the edge betweenness for an edge a is given by:

$$EB(a) = \sum_{o \in N} \sum_{d \in N; d \neq o} \frac{\sigma_{od}(a)}{\sigma_{od}} \tag{9}$$

where σ_{od} is the number of shortest paths from node o to node d and $\sigma_{od}(a)$ is the number of shortest paths from node o to node d that contain node a. The sum is computed for every couple of origin and destination nodes.

In typical applications, the edge betweenness is adopted for the analysis of graphs with unitary weights in order to gain insights on the topological structure of the graph. In this paper, however, we will consider the shortest paths over the traffic network in terms of the travel time associated to each edge, assuming a null potential flow.

Note that the above index is indeed valuable, since it provides insights on which links are more likely to be used independently on the particular origin and destination. Assuming a given amount of preexisting traffic, the edge betweenness can therefore be computed offline, in order to reduce the on-board computation time.

4 -Edge betweenness potential flow. The potential flow is computed assuming that for each link a, the flow generated will be a fraction of the saturation value, determined by the value of the edge betweenness $EB(a)$:

$$F_p(a) = EB(a)\,[c_a - F_a] \tag{10}$$

Let us now conclude the Section with a classification of the users and the definition of a peculiar satisfaction metric that accounts for both the length of the path and the preference parameter for each user.

3.2 User Profiling and Satisfaction Metrics

In order to facilitate the choice of the parameters for the users let us define a set of *user profiles,* based on a particular choice of the parameters α_u, p_u:

- *Optimistic*: the user evaluates its path without considering the potential flow and just choosing the nominal shortest path ($\alpha_u = 1$).
- *Pessimistic*: the user assumes that all the potential flow is distributed on or close to the nominal shortest path and calculates its shortest path on the bases of this assumption ($\alpha_u = 0$). The category is then divided in two subcategories:
  - *Slightly Pessimistic*: the user assumes the potential flow is distributed over the links of the shortest path but admits that a fraction of the users will spread on nearby links ($p_u = 3$).
  - *Strongly Pessimistic*: the user assumes the potential flow is all distributed on the shortest path (p_u=2).
- *Gambler*: a gambler user considers a random perturbation of the graph ($p_u = 1$) and a random α_u.
- *Smart*: the user considers the edge betweenness for the perturbation of the graph and $\alpha_u = 0.5$. The user decides to avoid the most used edges in the network independently on the current traffic situation; hence the Edge betweenness potential flow method ($p_u = 4$) is adopted.

Of course a profiling with a finer grain is also possible for instance by considering several choices of the parameter α_u for each of the above categories.

An important issue is how to measure the satisfaction of the users; in fact the definition of a satisfaction metric is the first step for the dynamic tuning of the parameters during the navigation.

Let us define the *objective satisfaction* metric S_u^{obj} as follows:

$$S_u^{obj} = \frac{s_{od}^*}{s_{od}^u} \tag{13}$$

where s_{od}^* is the length of the minimum path without considering the traffic flow generated by the users and s_{od}^u is the length of the path assigned to user u. Hence, the objective satisfaction is the inverse of the length of the path with respect to the minimum path.

In order to take into account the preferences of the users, let us define a subjective satisfaction metric S_u^{sub} as follows:

$$S_u^{sub} = \begin{cases} 1 & if\ S_u^{obj} = 1 \\ S_u^{obj}\left(\alpha_u \mu_{opt} + (1-\alpha_u)\,\mu_{pes}\right) & else \end{cases} \tag{14}$$

Unless the path found coincides with the theoretical minimum ($S_u^{sub} = 1$), the subjective satisfaction is scaled by a convex combination, based on α_u, of two parameters $\mu_{pes}, \mu_{opt} \in [0,1]$ which take into account the extremal cases (completely optimistic and completely pessimistic users). A possible choice of these parameters is $\mu_{pes} = 1$ and $\mu_{opt} = 0.5$. In this way the subjective satisfaction coincides with the objective satisfaction for a completely pessimistic user ($\alpha_u = 1$), while a completely optimistic user has a satisfaction that is scaled by μ_{opt} with respect to the objective one (e.g., half of the objective satisfaction). Eq. (13) implies that an optimistic user, choosing the theoretical minimum path, is less likely to be satisfied by a long route with respect to an optimistic one.

Note that the parameter μ_{opt} could also be assumed different for different users, thus representing a subjective choice, or could be dependent on the particular profile chosen.

4. Simulation Results

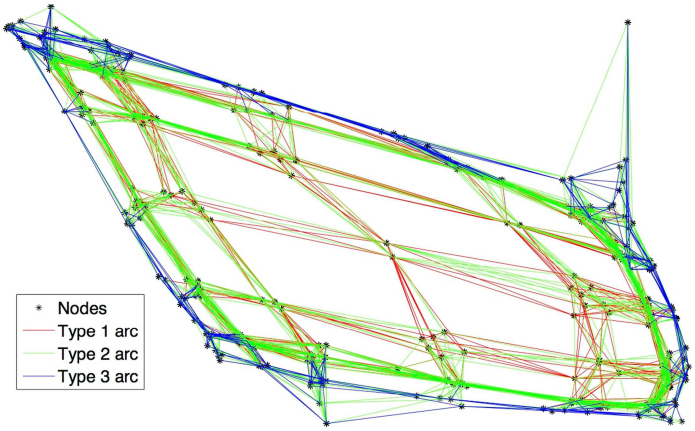

Fig. 1. Traffic network considered in the case study.

As shown by Figure 1, we consider a real traffic network with 329 nodes and 3369 edges, considering 3 typologies of edges:

- Type 1 (red): Capacity 2 users/s;
- Type 2 (green): Capacity 4 users/s;
- Type 3 (blue): Capacity 7 users/s.

Moreover, we assume a random current flow between 0 and half of the capacity of each edge.

We compare for different amount of users (from 10 to 1000 with a logarithmic spacing) the proposed approach with the *greedy strategy* (i.e., the routes are selected iteratively for the different users: at every step a user chooses the shortest path in the graph and the flow is updated according this choice and the graph is update; then the following user computes its path) and the *worst case strategy* (i.e., all the users take the same theoretical shortest path in the graph and the flow is updated considering all the users together).

Specifically, we consider the same origin and destination nodes for all the users and we choose the farther nodes as origin and destination (upper left and lower right nodes in Figure 1). In Figure 2 the results of the

comparison in terms of both average travel time and satisfaction are provided. More in detail, the leftmost figure shows the results for the average travel time: as shown by the picture, the proposed approach has an average travel time that is between the greedy and the worst case strategies for a small number of users; however, as the number of users grows, the proposed method shows its effectiveness by exploiting several different paths (up to 9 different paths are found by the proposed algorithm). The rightmost plot in Figure 2 shows the results in terms of satisfaction of the three methodologies; also in this case the average satisfaction of the proposed method tends to behave better as the size of the users grows, with respect to the others. In the aforementioned plot, the average subjective satisfaction for the proposed method is also reported; note that, according to the figure, such a value tends to be much more stable with respect to the objective satisfaction, implying that involving the preferences of the users in the choice of the route may prevent the users to quit the system.

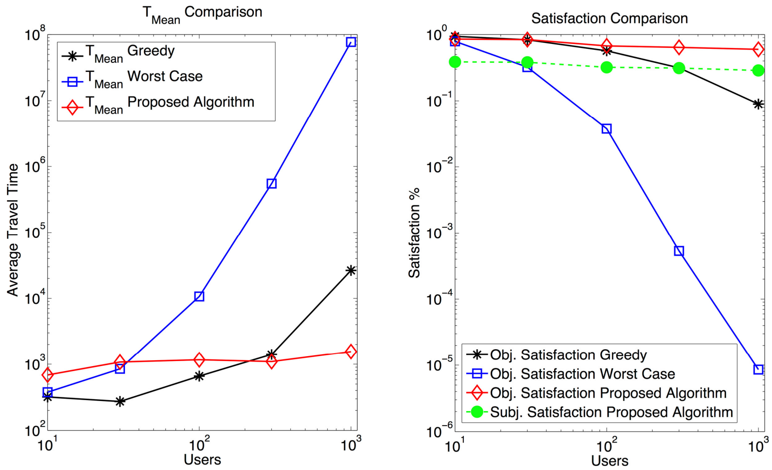

Fig. 2. Simulation results: the proposed algorithm (red line with diamonds) is compared with the greedy strategy (black line with asterisks) and the worst case (blue line with boxes) in terms of both average travel time (left) and average satisfaction (right) with respect to the number of users, assuming the same origin and destination for all the users. Moreover, the average subjective satisfaction of the proposed algorithm is given (green dotted line with filled circles). Results are the average of 50 runs.

5. Conclusions

In this paper a strategy for the distributed route guidance problem is provided. Within such an approach, the users are responsible for the choice of the parameters and therefore the risk of quitting the system is limited.

Moreover a satisfaction index is introduced, together with a profiling of the users based on the parameter choice.

The results show that the proposed methodology is indeed valuable since it results in a significant reduction of the average travel time while keeping the dissatisfaction of the users as much down as possible.

Future work will be devoted to extend the approach in the dynamic fashion by considering online adaptive parameters based on the user satisfaction during the navigation of the users.

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